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On an intelligent system to plan agricultural operations

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ABSTRACT

This paper focuses on the design and implementation of an intelligent system for planning operations of an agricultural robot. The aim of this intelligent system is to choose automatically the appropriate resources to execute certain agricultural operations, based on the user's preferences, as well as to define and schedule their sequence. The practical background is discussed, with descriptions of the solution space of agricultural applications and the way they can be restrained, through certain assumptions and decisions for minimizing the computing effort. The effectiveness of the intelligent system is demonstrated by comparing specific KPIs that have been calculated in the solution which would probably have been selected by a farmer and the solution proposed by the system, in different scenarios.

1. Introduction

In recent years, automation has been introduced into arable farming, altering traditional practice [1,2]. It is worth considering the environmental and socioeconomic aspects of this domain in order to realize the crucial role of a smart system, capable of optimizing the orchestration of the farming activities. According to a study by the Food and Agriculture Organization (FAO), the direct emissions, linked to agricultural activities, are approximately 10 % of the total greenhouse gas emissions [3], which tend to increase, by considering the coupling of farming with the food supply and the population growth. Additionally, the labour costs and shortage endanger the profitability of farming and even its survival. Similarly, the nature of agricultural activities is seasonal, which could be affected by labour scarcity, unexpected environmental and global events (COVID 19), as well as inappropriate planning, leading to food waste and insecurity, while causing financial losses [4]. It is also worth mentioning the challenges arising from the fertilizer prices and the financial pressure from inflation driving automation and the benefits accrued from it [4]. The technological evolution, mainly on the information and computer technology (ICT) domain, has triggered the development of smart farming systems, such as advanced or autonomous tractors and smart implements [5,6], making their scheduling and orchestration more flexible; nevertheless, even more complex. Another consideration is the rising demand for agricultural products, which necessitates more utilized fields, tractors and implements. These resources should work with both temporal and spatial efficiency such as a fleet of tractors, operating concurrently or sequentially, conducting tasks such as spraying and weeding, in diverse environmental conditions, i.e. wind or rain. Consequently, composing alternative scenarios for planning orchestration becomes increasingly complex and multidimensional. As an illustration of the above, an agricultural robotic system that uses dynamic route planning in four specific real-world farming scenarios has been described in [7].

All the aforementioned, indicate the need for a scheduling process in the framework of agricultural activities. Regarding the path planning, the traditional approach of the farmers, who prefer going lane by lane, or every other lane in case there are turning constraints, should be taken into consideration. In Fig. 1, there is such an example shown.

Nevertheless, the automation of the above method is not trivial task; it is an NP-Hard problem and in most of the cases, it is not feasible to seek the optimal solution [8]. A study by Santos et al. [9] analyses different path planning methods, in various agricultural applications and is defined by optimization criteria, system constraints and limitations as well as a dynamic behaviour, meaning that the plan is calculated

Abbreviations: KPI, Key Performance Indicators; AGV, Automated Guide Vehicles; IFAS, Intelligent FArming System.

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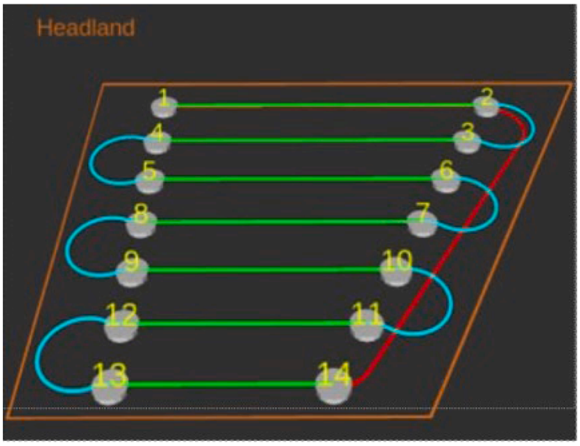

Fig. 1. Traditional way of passing through a field. The work starts at point 1. Green indicates working lanes, where the robot performs work; blue indicates how the robot turns from one lane into the next; and red indicates how the robot returns to the starting point.

offline or online. This analysis focuses on the micro-scheduling of the activities, namely on the way that the robot or tractor should traverse the field. Additional approaches are reported [8,10], through the prism of the already analysed NP-Hard problem, known as the Traveling salesman problem (TSP); nonetheless, without expanding the number of optimization criteria. A more macroscopic approach, regarding the work schedule optimization for agricultural robots is reported by Hizatate and Noguchi [11], where a genetic algorithm is used for the generation of the field path, for multiple robots, within the given constraints.

Nevertheless, despite the complexity of automating the path planning problem, efforts were made to approach this problem from different perspectives, based on a set of assumptions. An example is the comparison between two different approaches that has been conducted by Martin Filip et al. [12] as shown in Fig. 2. On the one side, they analysed the approach proposed by Bochtis and Vougioukas who used to solving the route planning problem based on simulated annealing [13] and on the other side they analysed the Conesa-Munoz approach, which combines the best known route optimization operators combined to form a new operator called mix-opt. The comparison between them is based on the headland distance and consequently on the total travel distance.

Other algorithms are focused on optimizing the manoeuvre time [14], by utilizing the heuristic Clarke–Wright savings algorithm [15]. Utamima and Reiners [16] have proposed a Fast Hybrid Algorithm (FHA) for the problem of Agricultural Route Planning (ARP). The algorithm combines elements from different routing strategies and heuristic methods and aims to minimize the non-working distance, travelled by the vehicles. The proposed solution has focused on 5 fields that surround a central workstation from which multiple vehicles start. Each field is covered by one vehicle at the time, but it may also be split into smaller fields, each of which will be covered by a separate vehicle, and thus reduce the time required to cover the entire field.

All the above approaches address isolated aspects of a complete agricultural planning system, but none of them is capable of solving the entire orchestration of resource allocation and task scheduling, at both high and low levels, considering multiple optimization criteria and dynamic performance in unexpected events. Additionally, it should be mentioned that in order to achieve high level of autonomy, a combination of other hardware and software components are required as well, such as advanced perception systems, motion controllers and trackers [17]. Nevertheless, the scope of this paper is mainly focused on the path planning systems.

In the manufacturing domain, the growing complexity and increased demand for adaptability and efficiency, within modern systems, requires the implementation of a sophisticated management system, capable of effectively planning multiple resources across various cases. Over the last decades, notable advances have emerged in the field of manufacturing, focusing on the aforementioned aspects. Chryssolouris has identified that need; to move from mass production to mass customization in order to cope with multiple manufacturing variants [18]. Michalos et al. [19] have conducted a review of the existing technologies and their challenges, by highlighting the important role of flexibility and adaptability to the domain of the automotive assembly lines. Likewise, in various areas, such as the aerospace manufacturing, single robots would decrease the system's efficiency and require a coordinated group of resources to ensure optimized efficiency of the executed operations and task parallelization [20].

In response to these challenges, intelligent systems have been developed in the manufacturing domain using AI-related methods. A dynamic scheduling on assembly systems has been implemented, by increasing the efficiency, while decreasing the assembly error and eliminating the need for human labour on planning tasks [21]. Likewise, Hu et al. have proposed a deep reinforcement learning method for real time Automated Guide Vehicles (AGV) scheduling on a flexible shop floor [22]. Liu et al. [23] have designed a solution to the Tree-Structured Task Allocation problem by using Group Multirole Assignment in order to satisfy some fixed relations among the tasks with very promising results. In addition, Feo-Flushing et al. [24] have implemented a system

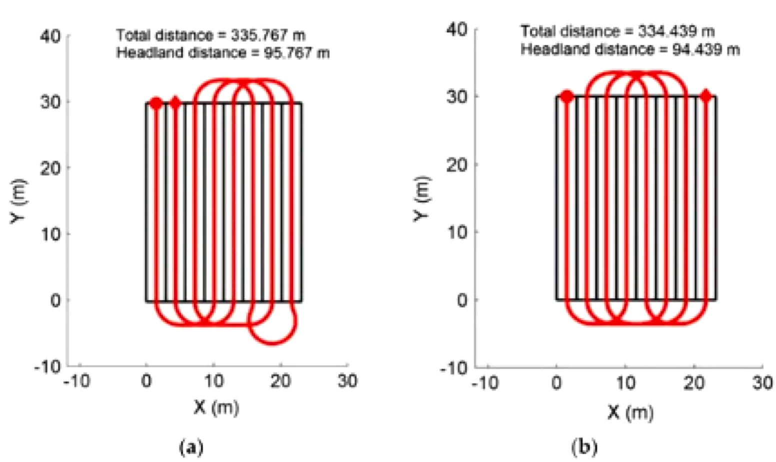

Fig. 2. Comparison of two plans as discussed by Martin Filip et al. [12] – On the left picture is the solution proposed by Bochtis and Vougioukas and on the right picture is the solution proposed by Conesa-Muñoz et al. The proposed solutions result on different calculations for the headland distance and therefore different total travel distance.

that handles task allocation, scheduling and control by combining the solution from a generic mixed integer linear program (MILP) solver and a trained genetic algorithm. In the same vein, Wang and Gombolay [25] showcase a novel graph attention network-based scheduler that relies on machine learning that enables near-optimal multi-robot scheduling in various sizes and capability.

From the above is clear that Artificial intelligence (AI) developments as well as their capability to address efficiently and in a cost-effective manner issues of the manufacturing field is becoming more common, while the manufacturing applications of AI related to manufacturing processes, robots, automation and manufacturing systems design and control have been heavily researched [26]. These concepts and developments have the potential to enhance the manufacturing domain, thus further research has been done so as to be applied to the agriculture domain as well.

The main objective of the work presented in this paper, is to adapt the intelligent approaches developed and applied in manufacturing domain, to address the specific challenges of the agricultural planning and scheduling.

2. Approach

As described in the previous section, the design of an intelligent system, capable of orchestrating scheduling and planning operations, for multiple fields and resources, is rather a complex activity. It requires to take into consideration a high level of data structuring and preparation, to consider the different parameters that are to be evaluated and affect the final outcome. Those parameters can be inserted and monitored by the user through a web-based interface and can split in two categories:

- Field characteristics
  - Waypoints
  - Working Lanes
  - Non-Working Areas
  - Transportation lanes
  - Special zones
  - Entry/Exit points of the field
- Resource characteristics
  - Tractor info: width, weight, model, position, max working/transportation speed, fuel tank capacity/consumption/level, mechanical interface, real time speed/position
  - Implement info: width, weight, model, position, real time speed/position, mechanical interface, consumable level

The above information is considered being the minimum requirement for any planning of farming activities, proided by the user through a custom UI. More details could be provided from the user for a specific field, such as areas which impose limitations on the vehicle (size, weight) or its movement (maximum speed, driving direction). The intelligent system doesn’t know whether these limitations may derive from soil conditions (e.g. wetness) or terrain characteristics (e.g. slope), but it only takes into account how the above parameters are afecting the decision criteria, such as time to complete the field, shortest distance, fuel economy etc. when choosing the best plan.

In order for the intelligent system to provide a planning solution, an inteligent search algorithm based on heuristics is used, developed for applications in the manufacturing domain and described in the work of Michalos et al. [27]. This search algorithm is using a set of decision parameters that enable searching the solution space quickly and with good quality of solutions for different sizes of problems. The scope of this paper is not to get into the details of this algorithm rather to present how such algorithms can be used in agriculture domain as well, apart from the manufacturing.

In Fig. 3, a grid-based model of the field is shown, demostrating some of the aforementioned parameters for the field. The grid-based approach as well as the size of each box that is suggested here enables the demonstration of the different parameters. More specifically, each box represents the same distance in the field but smaller box means that there is a type of “struggle” for the resource leading to a smaller speed and higher fuel consumption. Also, each box is highlighted with a different colour, representing a different part of the whole field. The connection between the field areas and the colours is elaborated below:

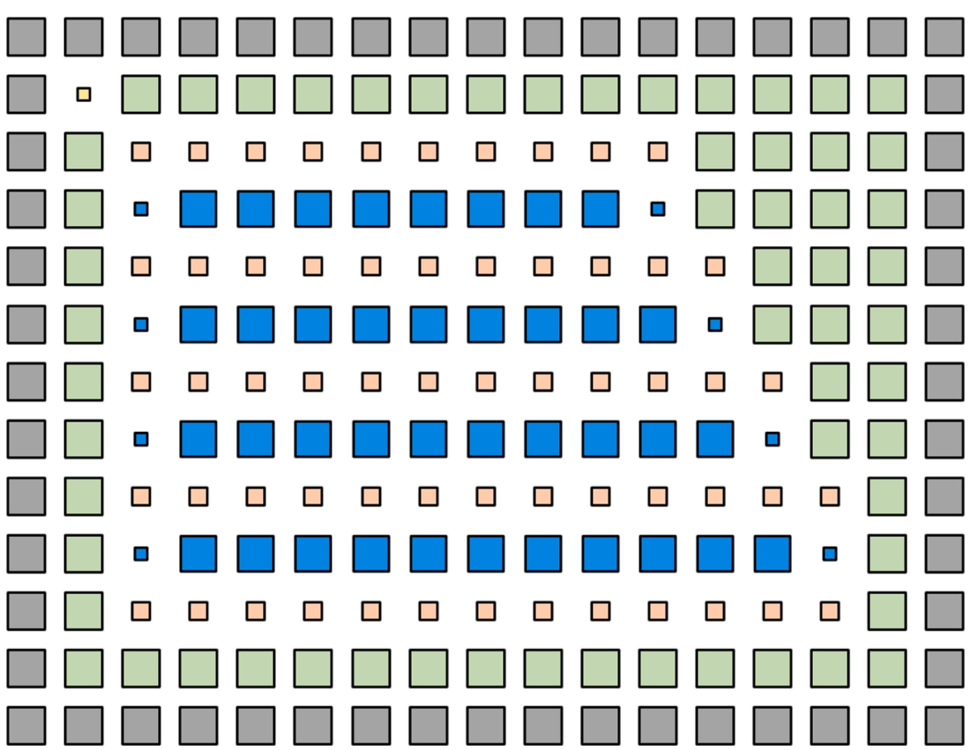

Fig. 3. Grid-based field representation where the different colours represent the different areas.

- Waypoints – Blue small boxes: Start and end points of a working lane.
- Working Lanes – Blue big boxes between the waypoints: AB lines composed from a sequence of big blue boxes, where the tractor should perform a farming operation.
- Non-Working Areas – Green boxes: the headland area in the field around the working lanes.
- Transportation lanes – Grey boxes: areas-lanes outside a specific field, used by the tractor to be transported from one field to another or from one field to the warehouse.
- Entry/Exit points of the field – Yellow small boxes: this is the area from which the tractor can enter and exit the field respectively.
- Plants – Beige boxes: areas where the actual plants exist and the tractor should not pass through.

The solution space in this case is defined by a set of points that should be placed in a specific order so as for the farming resources, such as tractors, to perform the farming operations in an efficient way, maximizing a set of Key Performance Indicators (KPIs), based on the user's requirements. These points could belong to the beginning or end of a work lane (waypoints), they could be the entry/exit of a field, or they could be supporting points within a non-operational (headland) or transport area. Thus, it is clear that the solution space is large and unstructured and consequently a deterministic search is not feasible and therefore, we use the heuristic search algorithm.

Additionally, in order to simplify the calculations, an assumption has been made, which is that once a waypoint of a lane has been selected, then the system should select the other one belonging to the same lane as well, ensuring that the tractor does not just pass by a waypoint, but actually chooses and passes through the specific lane. Neither passing-by from one waypoint without completing its lane or driving backwards is allowed.

Having the above in mind, the intelligent heuristics-based method has been used for searching among the best solutions, suggesting a "good-enough" solution among the best solutions based on a predefined criterion selected by the user. As described in the work of Michalos et al. [27] such intelligent algorithms can minimize the computational resources and time required to obtain the result. The proposed system of this paper is called **I**ntelligent **FA**rming **S**ystem (IFAS) and its architecture is visualized in Fig. 4. In its core, is the backend system that is based on heuristics, and contains a database, where all the data and system states have been stored into. The user is able to upload information to the system through a user-friendly UI, as well as to visualize the result of the intelligent planner. Once the user has a plan, its implementation unit is responsible for sending it to the resources for execution. Last but not least, sensor data are visualized and stored during the execution phase, depending on the hardware installed on the machine, enabling the farmer to have a clear view of the agricultural operations. Examples of such data are real time GPS data and resources' speed, live view of the field through an onboard camera which provides raw data, fuel or spray level, data coming from the implement such as the weeding quality or spraying quantity etc.

3. Application scenarios

For the scope of this paper, in a python script three adjacent fields have been created based on the modelled described in the previous section and will be utilized for the application scenarios (Fig. 5). As described above, in each field, the working lanes are visualized with blue lines, while the headland area is represented by the green boxes around them. Furthermore, the entry and exit points of the field are represented by the yellow box, which acts as the starting and end point of all paths. The size of each box is connected with the ground inclination, defining special zones within the field where the tractor cannot use its default speed.

Following the definition of the fields, specific KPIs, namely distance, time and fuel consumption, are calculated for travelling from one point to another in any field. The selection of a "good" alternative is related on these calculations since the aim is to have minimized values for the KPIs. In this paper, 4 cases are evaluated via a comparison of the KPIs, between a path intuitively chosen by the farmer and the optimal path that has been generated by IFAS. The cases that will be discussed are the following:

- A path followed by a single tractor in one field.
- A path followed by a single tractor in two fields.
- A path followed by two tractors in two fields.

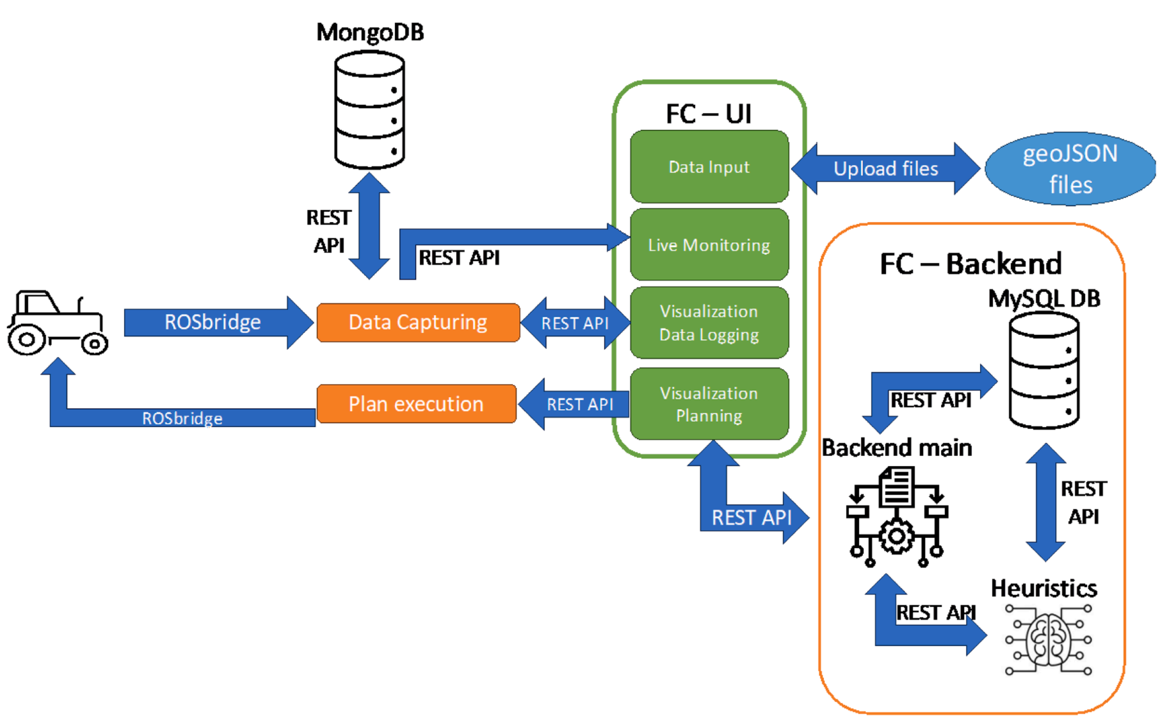

Fig. 4. Intelligent Farming System (IFAS) architecture.

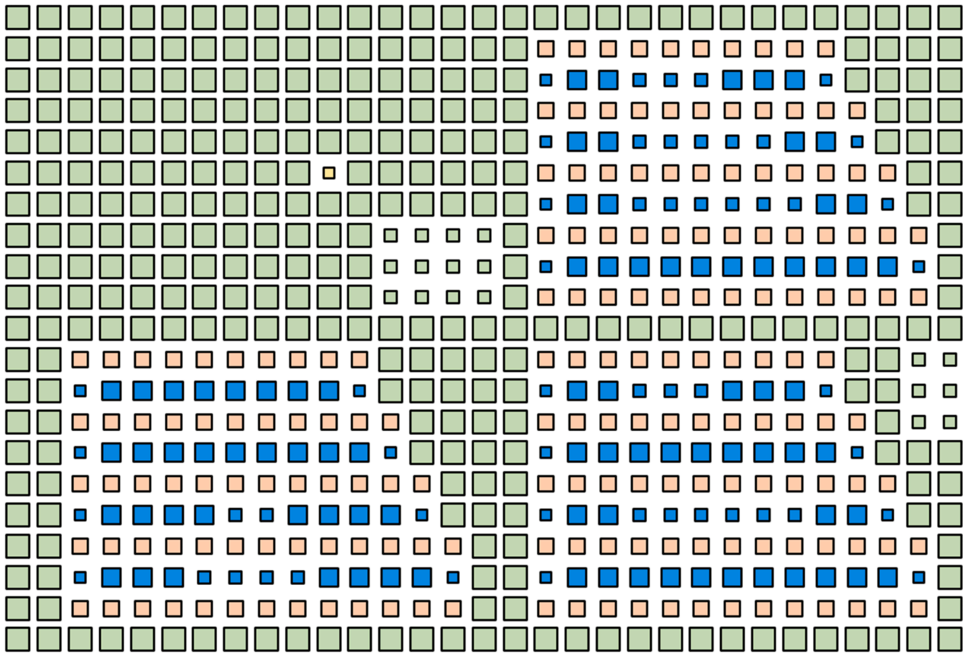

Fig. 5. Three adjacent fields to generate alternative application scenarios where the size of each box represents the speed the tractor can have.

- A path followed by two tractors in three fields.

For the first case, where the first field has been assigned to Tractor 1, the lane sequence that the farmer would typically follow is shown in Fig. 6, with the numbers in the cells to represent the steps the farmer would follow in the field, while each box represents a 100m-segment of the field.

For the same case, the path generated by IFAS is shown in Fig. 7.

For the second case, where both fields have been assigned to Tractor 1, the lane sequence that the farmer would follow is shown in Fig. 8.

For the same case, the path generated by IFAS is shown in Fig. 9.

For the third case, where each field has been assigned to Tractor 1 and Tractor 2 respectively, the lane sequence that the farmer would follow is shown in Figs. 10 and 11.

For the same case, the path generated by IFAS is shown in Figs. 12 and 13.

For the last case, where three fields should be assigned to Tractor 1 and Tractor 2, the lane sequence that the farmer would follow is shown in Figs. 14 and 15

For the same case, the path generated by IFAS is shown in Figs. 16 and 17.

4. Results & discussion

IFAS enables the farmer to configure the specifications of the agricultural scenario, namely define the number of fields or lanes the

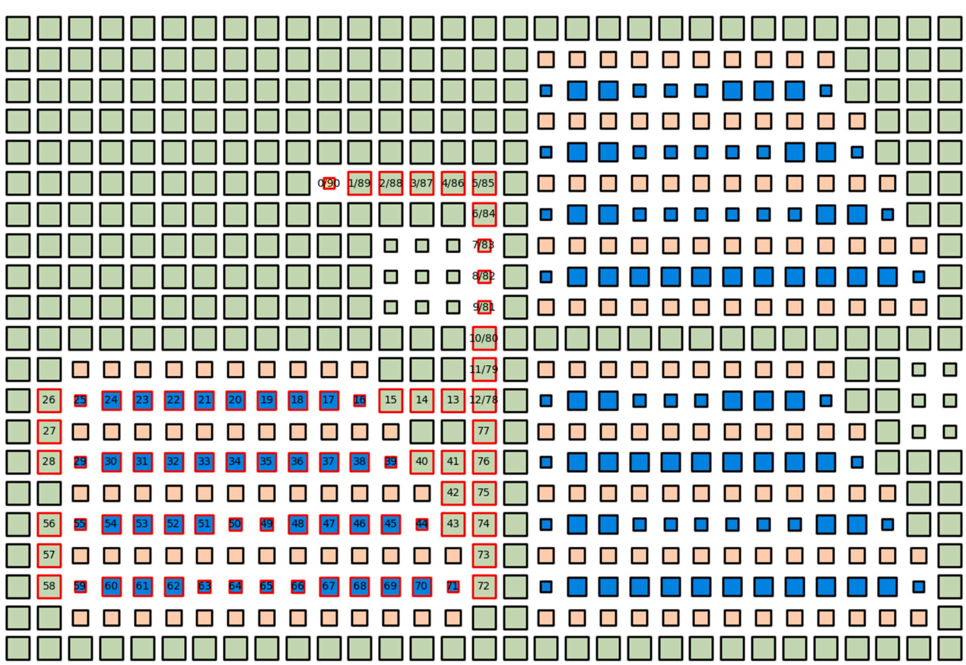

Fig. 6. First case – Path inside the field, intuitively followed by a farmer, the numbers in the cells represent the steps the farmer would follow in the field.

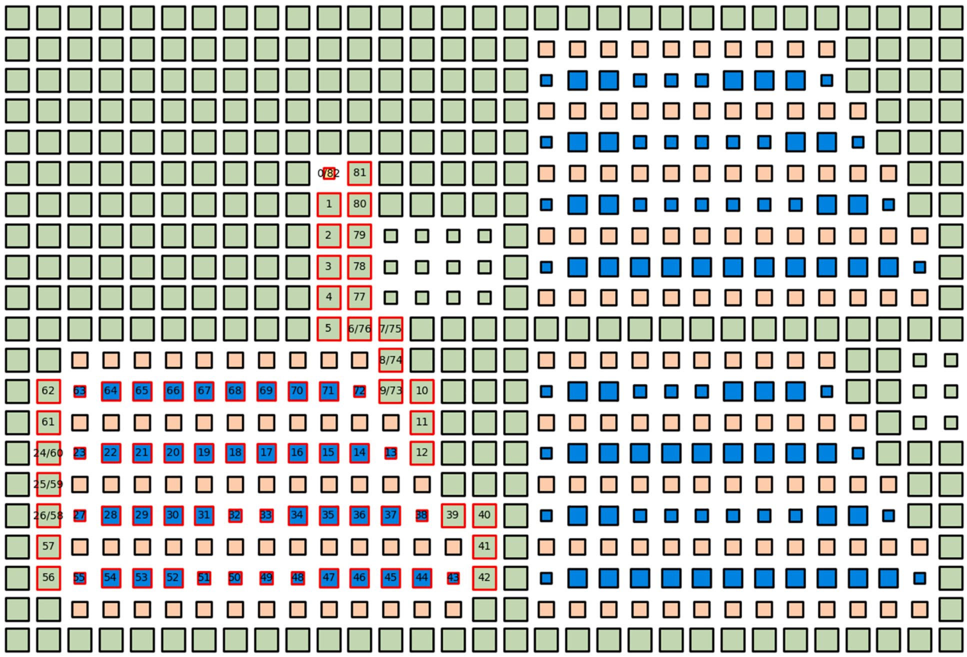

Fig. 7. First case – Path inside the field, generated by the IFAS, the numbers in the cells to represent the steps the farmer would follow in the field.

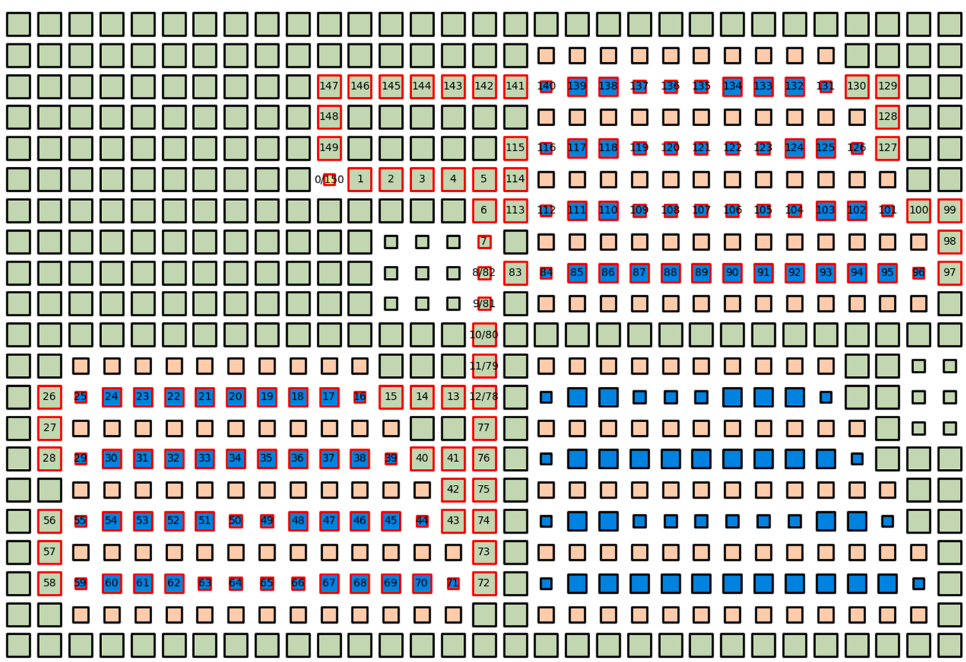

Fig. 8. Second case – Path inside the field, intuitively followed by a farmer, the numbers in the cells represent the steps the farmer would follow in the field.

tractors should work on, what type of a process needs to be performed and the optimization criterion based on which the solution will be provided, i.e. quickest path based on time or shortest path based on distance. Then, the result provided by IFAS is the automatic assignment of each lane or field to the appropriate resources and the automatic scheduling of the lanes, namely the order in which they should be processed, so as for a "good" result to be achieved, according to the aforementioned criterion selected by the farmer.

Focusing on the planning dimension of the proposed system, the farmers take different approaches, both in literature and in practice. More specifically, the farmers prefer to follow the sequential approach, in order to avoid losing any lane unprocessed, without taking into consideration the benefits that could be accrued in terms of KPIs had they followed a more sophisticated path, as shown in Fig. 1.

Multiple methods or even combinations of those are used in the literature, that prioritize different aspects for optimization, such as finding the smaller headland and total travel distance or finding the shortest manoeuvring time or use algorithms like the Fast Hybrid Algorithm (FHA) which tries to minimize the non-working distance travelled by the tractors. The system proposed in this paper has a more holistic approach compared to the other systems from the literature, with the advantage of having the possibility to address multiple scheduling criteria, instead of focusing only on one, by giving different weights on them. The aforementioned algorithms are rather close to the

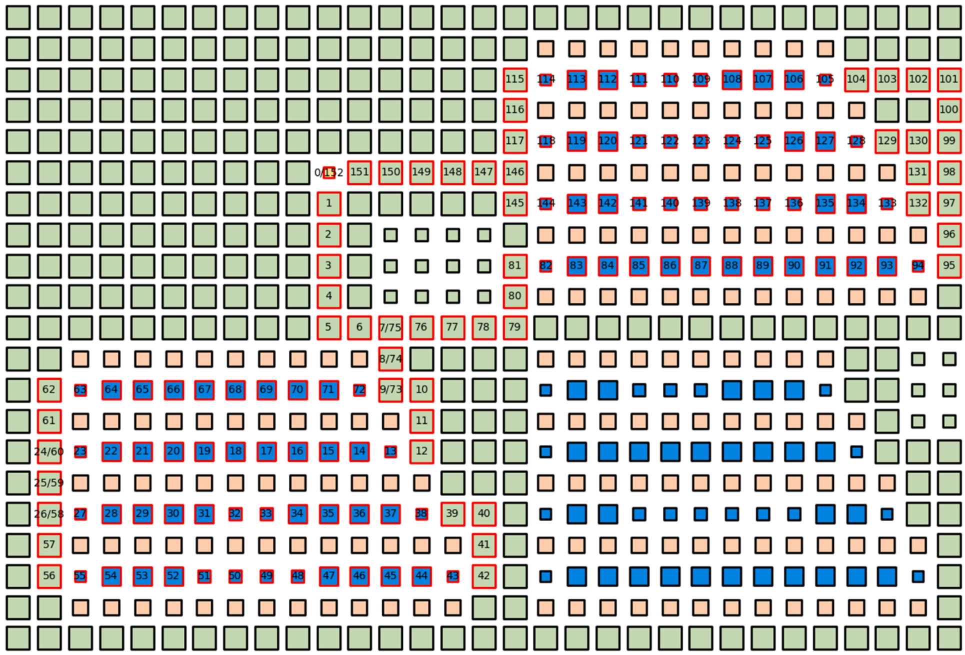

Fig. 9. Second case – Path inside the field, generated by IFAS, the numbers in the cells represent the steps the farmer would follow in the field.

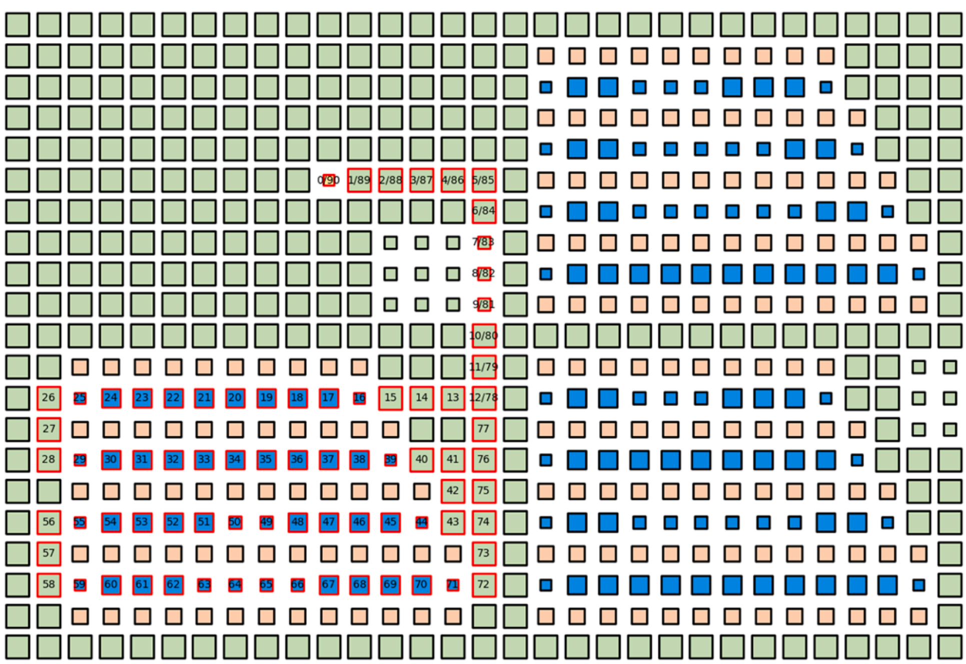

Fig. 10. Third case: Tractor 1 – Path inside the field, intuitively followed by a farmer, the numbers in the cells represent the steps the farmer would follow in the field.

one discussed in this paper, but they are not as flexible..

Regarding the scenarios presented in this paper, as discussed the KPIs calculated are time, distance and fuel consumption. Although there are multiple fields and resources, there is a single starting point for all the resources and the only criterion is minimize the non-working distance of these resources, without taking into consideration other KPIs, such as time or fuel consumption. The calculated KPIs for each scenario have been summarized in the table below, followed by an analysis for each case. The calculation for the distance was based on the number of boxes, where each box represents 100 m distance as already mentioned in Section 3, for the time is based on the speed in the different areas (working speed 2,52 m/s, non-working speed: 4 m/s and red zone speed limitation: 1,64 m/s) and for the fuel consumption is based on the type of area (working lanes 9 l/h, non-working lanes: 4 l/s and red zone speed limitation: 13 l/h).

As shown in Table 1, the overall IFAS provides a path with better KPIs, namely time, distance and fuel consumption, compared to the standard sequential approach usually followed by the farmers, even very complex scenarios such as case 4, where multiple fields and vehicles should be planned. More specifically, the execution time is always lower between the two executions, although in some cases this difference is rather small. On the other side, the distance difference is rather

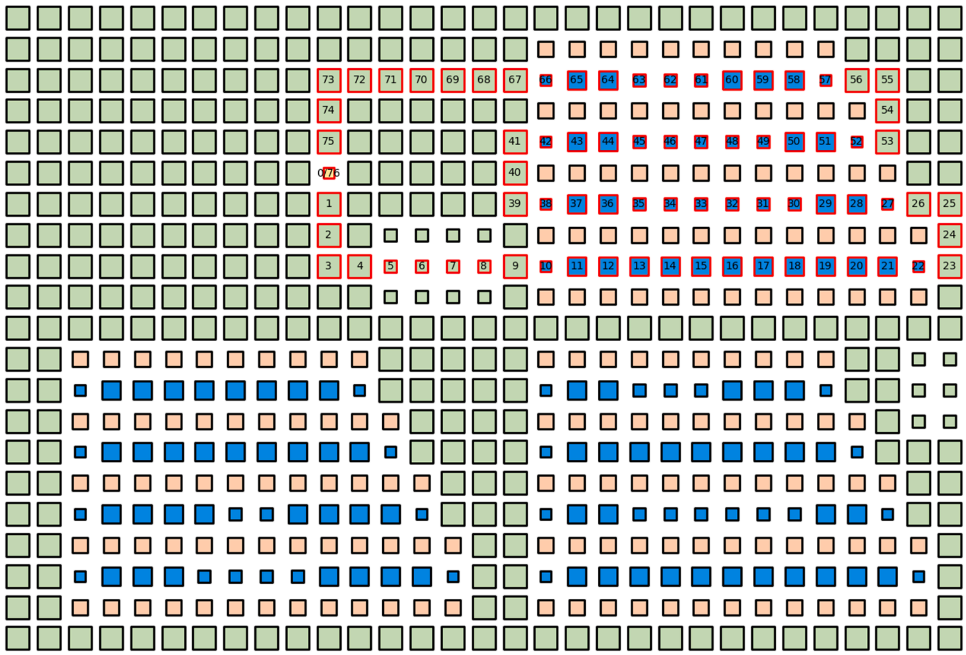

Fig. 11. Third case: Tractor 2 – Path inside the field, intuitively followed by a farmer, the numbers in the cells represent the steps the farmer would follow in the field.

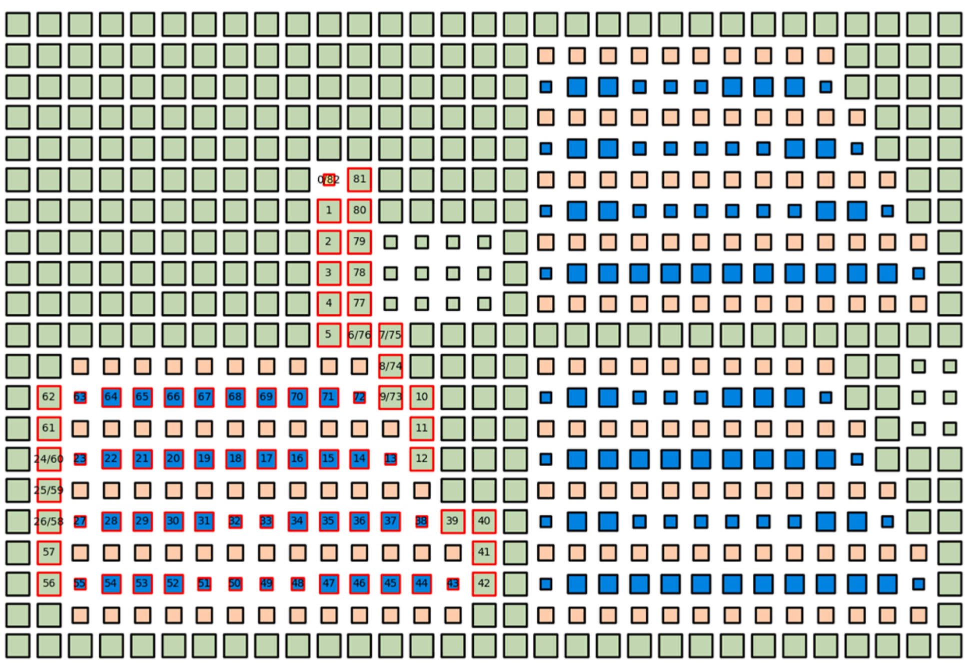

Fig. 12. Third case: Tractor 1 – Path inside the field, generated by IFAS**,** the numbers in the cells represent the steps the farmer would follow in the field.

significant, reaching in some cases the 800 m, which could have an important impact on certain parameters, such as the soil compaction. Similar to the time, it is worth mentioning that the fuel consumption has always been minimized, reaching in some cases a saving more than 1 litre.

In the second case, there is an improvement in time and fuel consumption, but not in distance. Consequently, this gives flexibility to the farmer, depending on his needs, to choose a different alternative solution, or the KPI he wants to prioritize – time over distance or otherwise. On a similar note, in the third and fourth cases, tractor 2 covers the same distance, but the time as well as the fuel consumption are improved in the solution proposed by IFAS. This is because the path could not be shortened any further, thus leading to the improvement of the other two KPIs.

From the above, the benefits of the intelligent planner are clear, with the most critical being the high level of flexibility it offers the farmer. The user can give input on the KPI that he wants to prioritize, letting the system suggest a solution, which meets his requirements. Farmers who do not implement any automation tools, follow the same route every time they need to perform an agricultural operation, regardless of the type of work they have to perform or without taking into consideration other parameters of the field's condition, such as the soil, the weather

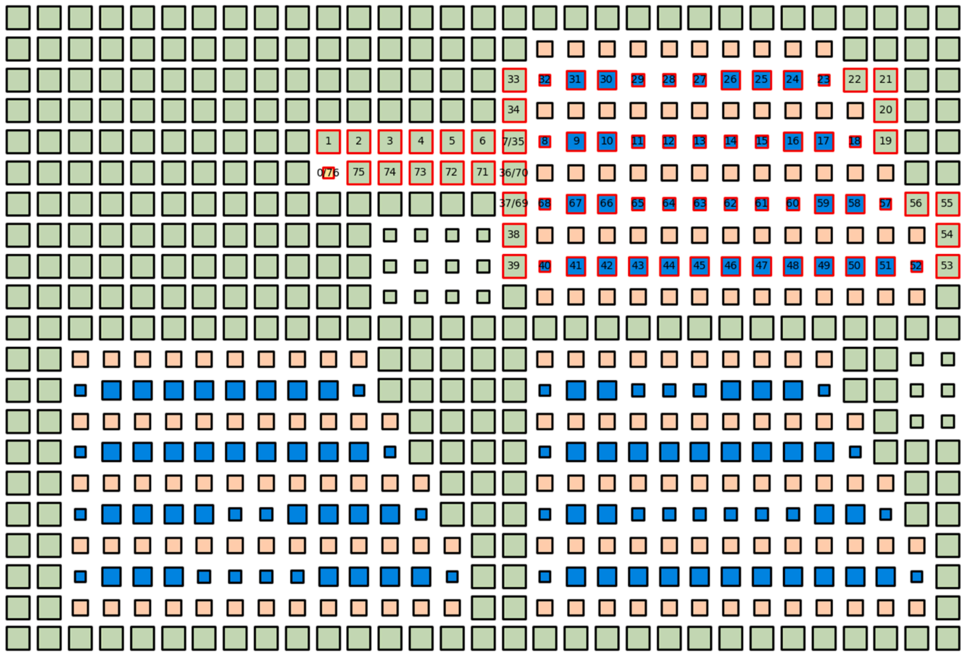

Fig. 13. Third case: Tractor 2 – Path inside the field, generated by IFAS, the numbers in the cells represent the steps the farmer would follow in the field.

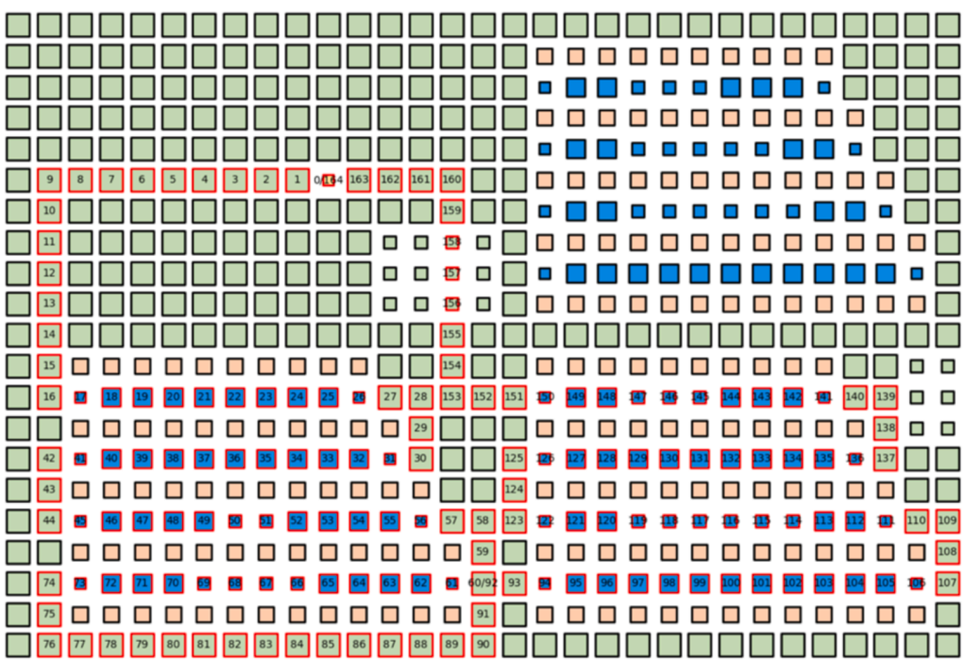

Fig. 14. Fourth case: Tractor 1 – Path inside the field, intuitively followed by a farmer, the numbers in the cells represent the steps the farmer would follow in the field.

conditions, the number of fields or lanes etc. An intelligent system that can take such parameters into consideration, could provide a solution that better meets a farmer's needs.

The intelligence of IFAS is depicted in the diagrams below (Figs. 18 and 19), in which the fuel consumption and the speed are shown for each 100 m-segment of the field. These diagrams stem from the first case and can be seen that the farmer crosses four times from special areas with deviations of speed, thus in time and in fuel consumption, while the IFAS suggests a route that crosses three times such areas leading to better results in terms of distance and time fuel consumption.

Another advantage of IFAS is that it addresses both the resource assignment and the task scheduling for agricultural activities; an aspect that has not been addressed in the literature. This offers a more holistic approach to the planning problem of agricultural operations, by removing the cognitive load from the farmer, who, in the case of other approaches, would have to do a post-processing of the result in order to be able to perform the agricultural operation.

Furthermore, regarding the task scheduling, the state-of-the-art frameworks emphasize on specific criteria, i.e. finding the shortest or fastest path, by providing limited options to the user and eliminating combinability, i.e. by finding the best option that combines the shortest path and the lowest fuel consumption. In this way, it is clear that the

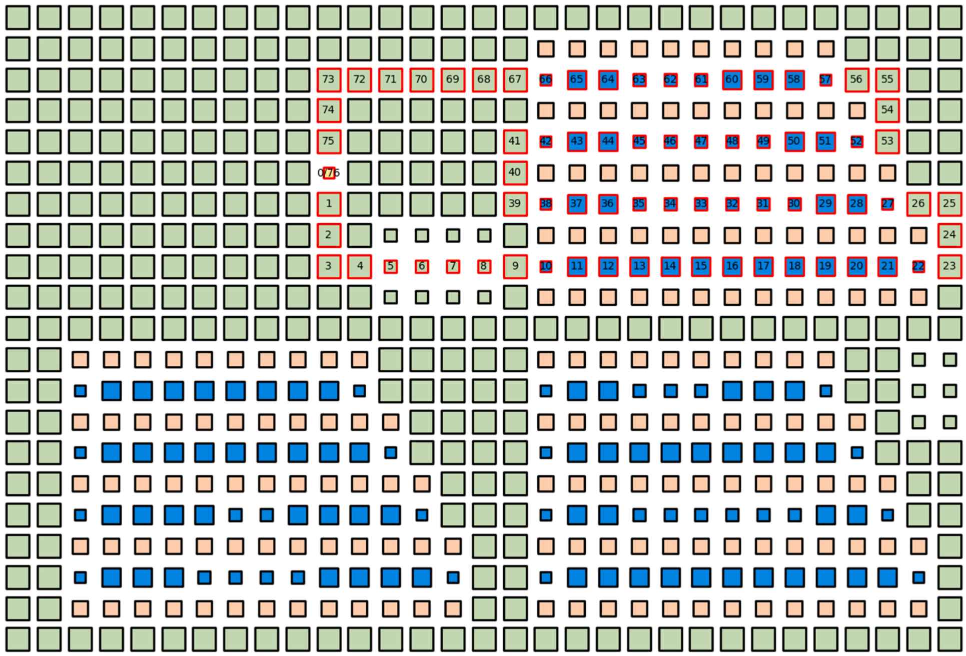

Fig. 15. Fourth case: Tractor 2 – Path inside the field, intuitively followed by a farmer, the numbers in the cells represent the steps the farmer would follow in the field.

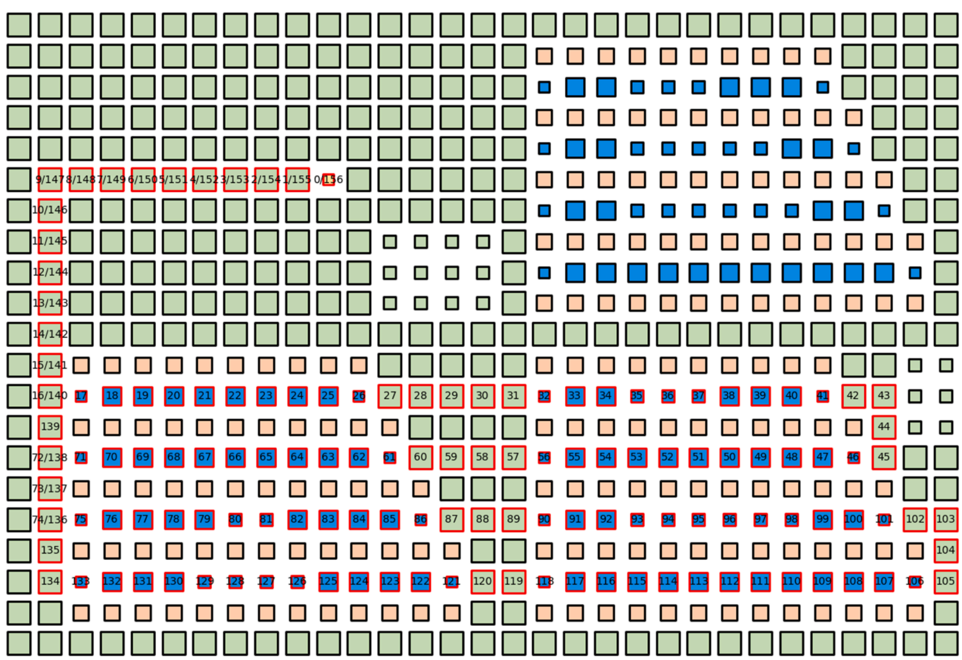

Fig. 16. Fourth case:Tractor 1 – Path inside the field, generated by IFAS, the numbers in the cells represent the steps the farmer would follow in the field.

level of flexibility, in terms of generating personalized results, is rather limited. With the proposed system, the user is able to add more aspects and prioritize or even combine the most important ones, by fine-tuning their impact.

Moreover, the intelligent system calculates and provides metrics to the farmer for the proposed solution. This can raise awareness about other aspects, namely fuel consumption, amount of spraying, the CO2 emissions etc. helping to develop a more environmentally friendly and sustainable attitude. Other methods that make such calculations are not as mature or advanced to take up more complex parameters, such as those mentioned above; they focus more on time and the distance travelled.

Last but not least, the advantage of the proposed system is that it follows certain assumptions that do not compromise the outcome but greatly minimize the number of possible solutions. Moreover, although an exhaustive evaluation could provide the best solution, it would require large computational power and time. The use of heuristics helps the system reduce the computational power and the time required to provide a "good" solution among the best possible ones.

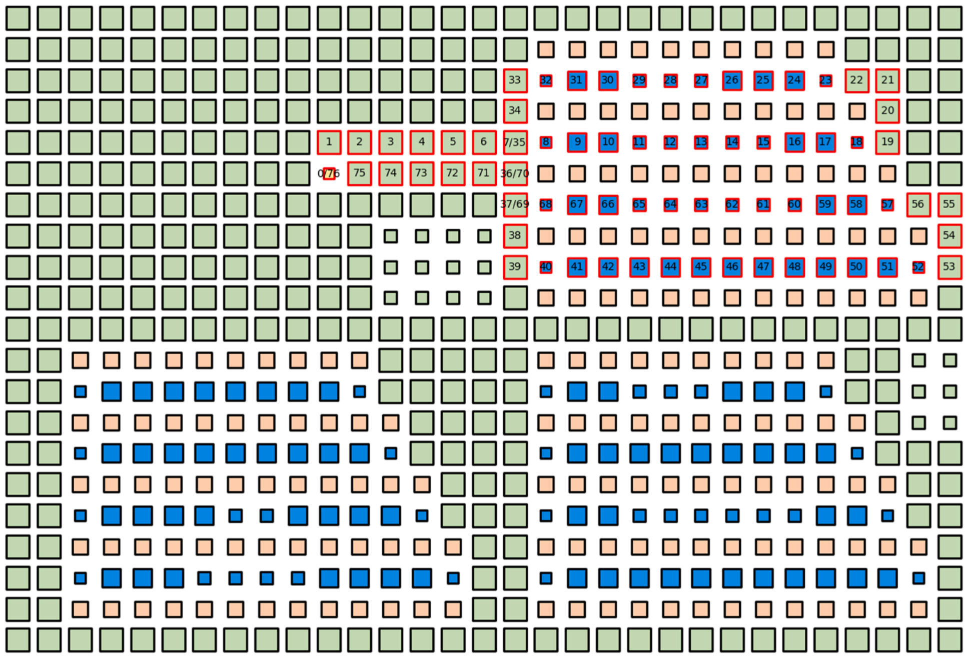

Fig. 17. Fourth case:Tractor 2 – Path inside the field, generated by IFAS, the numbers in the cells represent the steps the farmer would follow in the field.

Table 1
KPIs for all the cases.

Scenario	Farmer's approach	IFAS
Case 1: 1 field – 1 Tractor	Time: 2947 s Distance: 9100 m Fuel consumption: 7 litres	Time: 2567 s Distance: 8300 m Fuel consumption: 5.8 litres
Case 2: 2 fields – 1 Tractor	Time: 5067 s Distance: 15,100 m Fuel consumption: 12.6 litres	Time: 4938 s Distance: 15,300 m Fuel consumption: 11.7 litres
Case 3: 2 fields – 2 Tractors	Tractor 1 Time: 2947 s Path length: 9100 m Fuel consumption: 7 litres Tractor 2 Time: 2675 s Distance: 7700 m Fuel consumption: 7 litres	Tractor 1 Time: 2567 s Path length: 8300 m Fuel consumption: 5.8 litres Tractor 2 Time: 2531 s Distance: 7700 m Fuel consumption: 6.3 litres
Case 4: 3 fields – 2 Tractors	Tractor 1 Time: 5346 s Path length: 16,500 m Fuel consumption: 12.6 litres Tractor 2 Time: 2675 s Path length: 7700 m Fuel consumption: 7 litres	Tractor 1 Time: 5038.027 s Path length: 15,700 m Fuel consumption: 11.8 litres Tractor 2 Time: 2531 s Path length: 7700 m Fuel consumption: 6.3 litres

5. Conclusion

An intelligent planner (IFAS) that can provide resource assignments and agricultural task scheduling, using as input multiple resources and fields, has been discussed. IFAS offers the user the flexibility to select the pool of fields and resources he/she wants to work on and find a solution among the best alternatives, according to the defined criteria. The high flexibility and the holistic approach are the main features of the method described, while for future work, the execution of the intelligent system, drawing information from a group of real fields and real resources, has been planned in order to better display its benefits.

The authors ensure the following ethical statemens

They have written entirely original works, and no work or words of others have been used.

Proper acknowledgment of the work of others has been given, citing their publications, that have influenced the reported work and that give the work appropriate context within the larger scholarly record.

They ensure that there is no plagiarism in any of its forms.

No similar manuscripts have been published, describing essentially the same research in more than one journal of primary publication.

No information in this manuscript has been obtained in the course of confidential services.

Authorship has been limited to those who have made a significant contribution to the conception, design, execution, or interpretation of the reported study. All those who have made substantial contributions have been listed as co-authors.

No generative AI or AI-assisted technologies has been used to create content for this manuscript in any format, either text or image.

CRediT authorship contribution statement

Panagiotis Karagiannis: Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Panagiotis Kotsaris:** Writing – original draft, Visualization, Validation, Software, Investigation. **Vangelis Xanthakis:** Software, Methodology, Conceptualization. **Panagiotis Vasilaros:** Writing – original draft, Software, Investigation. **George Michalos:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Sotiris Makris:** Writing – review & editing, Supervision, Project administration, Conceptualization. **Frits K. van Evert:** Writing – review & editing, Project administration, Conceptualization. **Ard T. Nieuwenhuizen:** Writing – review & editing, Conceptualization. **Spyros Fountas:** Writing – review & editing. **George Chryssolouris:** Writing – review & editing, Supervision, Methodology, Conceptualization.

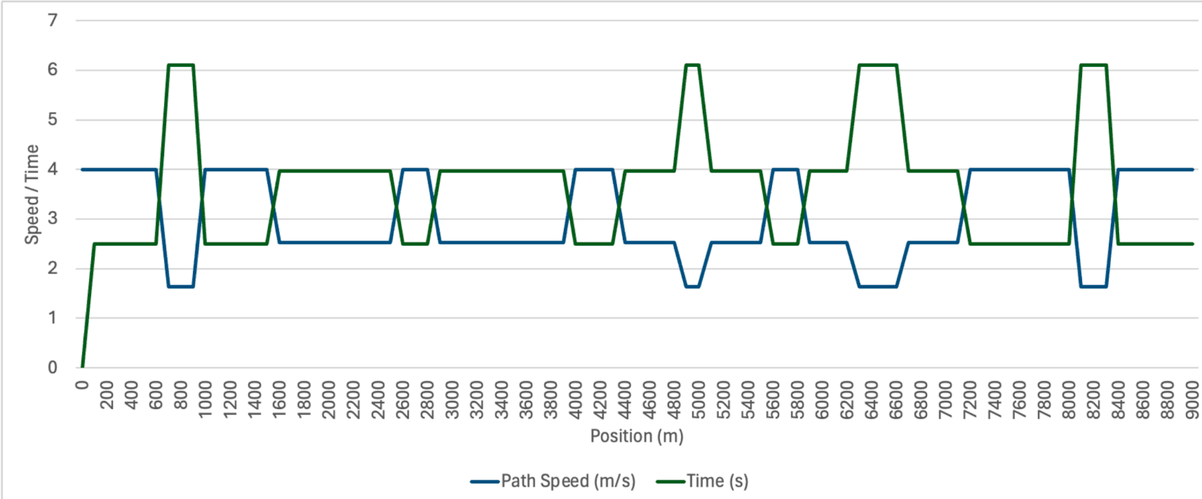

Fig. 18. Diagram showing how the different metrics change every 100 m in the field - Manually followed by a farmer.

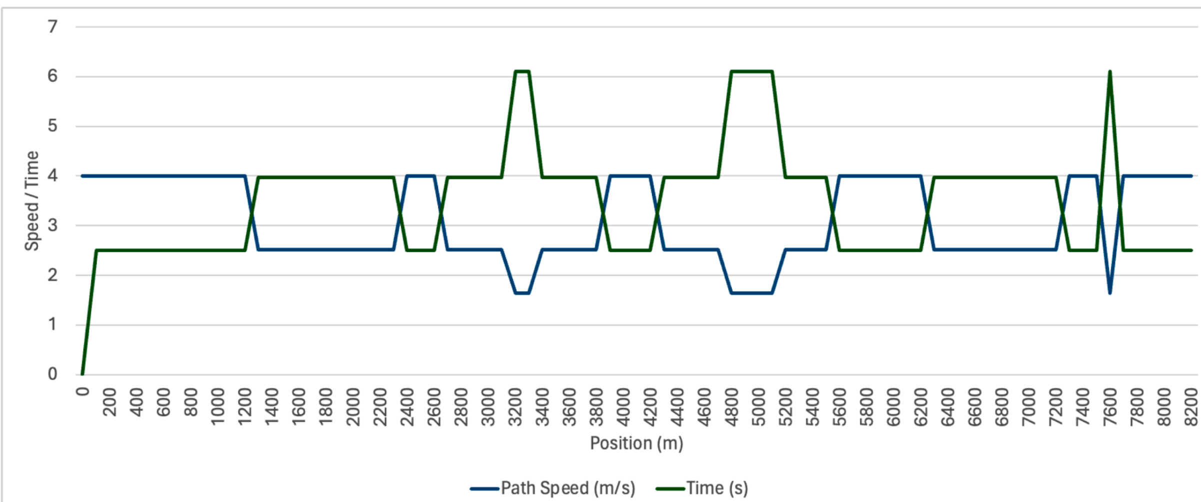

Fig. 19. Diagram showing how the different metrics change every 100 m in the field - Generated by IFAS.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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